ROBUST DECORRELATING MULTIUSER DETECTION IN THE PRESENCE OF ALPHA-STABLE CHANNEL NOISE

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ABSTRACT

In this paper, robust decorrelating detectors for DS-CDMA communication systems with the α-stable channel noise are presented. The proposed detectors are derived using two optimization criteria: the least l_p norm (LP) and the maximum likelihood (ML) criterion. The robust decorrelating multiuser detection schemes are implemented in an iterative form (with use of the IRLS algorithm), as well as in an adaptive one (with use of the RWLS algorithm). In order to compare these schemes with the conventional non-robust method, computer simulations are carried out. They show that all considered robust detectors significantly outperform the non-robust detection technique. The obtained results of Monte Carlo simulations show also relations between performance of the proposed iterative and adaptive detectors in near-far situation, as well as for different levels of channel noise impulsiveness.

1. INTRODUCTION

The direct sequence code division multiple access is a mainstream multiple-access method applied in the third generation (3G) wireless communication systems [1]. Capacity of DS-CDMA systems, considered as the number of users that can simultaneously communicate with a specified level of performance, is soft-limited by multiple-access interferences (MAI) between the users. MAI arise for lack of orthogonality of signature sequences assigned to particular users in the system [2]. A number of techniques have been proposed to mitigate deterioration of system performance caused by MAI. Some of these techniques, such as spreading sequence design, forward error correction (FEC) or power control algorithms (PCA), are now used in commercial 3G systems. Other advanced methods combating MAI, like multiuser detection (MUD), smart antennas and space-time processing are mentioned in 3G system specifications as options, and it seems probable that they will be soon implemented [3].

The optimal maximum likelihood (ML) sequence detection method for DS-CDMA systems has been proposed by Verdú [2]. Unfortunately, the Verdú's optimal detector has two essential disadvantages: it requires full knowledge of parameters of interfering users' signals and its computational complexity grows exponentially as the number of users increases. Many suboptimal detection schemes have been proposed since Verdú's fundamental work was published. However, derivation of these detectors is usually based on the assumption that the ambient channel noise is Gaussian. In fact, in many physical channels, the ambient noise turns out to be decidedly non-Gaussian and has the impulsive nature. Especially, experimental measurements of the noise distribution in real wireless channels confirm its impulsiveness [4].

Recently, one can find more and more works which deal with the robust multiuser detection [5], [6], [7], [8], [9]. In most of them, it is assumed that the channel noise is adequately modeled by a two-term Gaussian mixture distribution with exponential tails, which belongs to the set of ε-*contaminated Gaussian distributions* [10]. For that reason, many of robust MUD techniques employ the M-estimation method [5], [7]. However, the results of measurements show that the distribution of an electromagnetic noise in urban environments has heavier than exponential tails, and may be approximated by the α-stable distributions [11]. Performance of multiuser decorrelating detectors in the presence of the α-stable channel noise has been studied in [7] and [8]. In both cases, the detection schemes were based on the M-estimation method.

In this paper, two robust decorrelating detectors for DS-CDMA systems with the α-stable channel noise are proposed. They are based on minimizing specific cost functions for robust regression: the l_p norm of estimation errors, and the function derived from the maximum likelihood estimation criterion. In the latter case, it is assumed that the channel noise is modeled by the Cauchy distribution ($\alpha = 1$).

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The paper is organized as follows. In Sec. 2, the model of signal in the DS-CDMA communication system is introduced. In Sec. 3, the proposed robust decorrelating detectors are derived. Some implementation issues are addressed in Sec. 4. Performance of various detectors is verified via simulations in Sec. 5. In Sec. 6, some concluding remarks are given.

2. SIGNAL MODEL

Let us consider an asynchronous DS-CDMA communication system with K active users operating with the coherent binary phase-shift keying (BPSK) modulation format. The waveform $r(t)$ at the input of the receiver can be modeled as superposition of modulated data signals related to individual users, and observed in additive channel noise $w(t)$

$$r(t) = \sum_{k=1}^{K} A_k \sum_{i=0}^{M-1} b_k(i) s_k(t - iT_b - \tau_k) + w(t), \quad (1)$$

where T_b is the symbol interval and M is the length of the data frame of interest. A_k, τ_k, $\{b_k(i); i = 0, 1, ..., M-1\}$ and $\{s_k(t); 0 \le t \le T_b\}$ denote the received amplitude, delay, symbol stream and normalized signature waveform of the kth user, respectively. For each k, $\{b_k(i)\}$ is a sequence of M independent binary random variables (RV) taking on equiprobable values 1 or -1. Signature waveform $s_k(t)$ is supported on interval $[0, T_b]$, has unit energy, and is given by

$$s_k(t) = \sum_{n=0}^{N-1} a_n^{(k)} p_{T_c}(t - nT_c), \quad t \in [0, T_b], \quad (2)$$

where N is the spreading factor, $\{a_0^{(k)}, \dots, a_{N-1}^{(k)}\}$ is the binary-valued spreading code of the kth user, and $p_{T_c}(t)$ is the normalized chip waveform of duration $T_c = T_b/N$.

We restrict now our attention to the synchronous case of model (1), i.e., we assume that $\tau_1 = \tau_2 = \cdots = \tau_K = 0$. In the synchronous setup, to detect the symbols of all K users in the ith symbol interval it is sufficient to analyze the signal which is received during the ith signaling interval, i.e.

$$r(t) = \sum_{k=1}^{K} A_k b_k(i) s_k(t - iT_b) + w(t), \quad t \in [iT_b, (i+1)T_b]. \quad (3)$$

At the receiver, signal (3) is chip-matched filtered and sampled at the chip rate ($1/T_c$). As a result, we obtain the discrete-time signal model which can be written in the following concise matrix form

$$\boldsymbol{r}(i) = \boldsymbol{S}\boldsymbol{A}\boldsymbol{b}(i) + \boldsymbol{w}(i), \quad (4)$$

where $\boldsymbol{r}(i)$ is the $N \times 1$ vector of the received sampled signal, $\boldsymbol{S} \triangleq [\boldsymbol{s}_1 | \cdots | \boldsymbol{s}_K]$ is the $N \times K$ spreading matrix, $\boldsymbol{s}_k \triangleq [s_0^{(k)}, \ \dots \ , s_{N-1}^{(k)}]^T = \frac{1}{\sqrt{N}}[a_0^{(k)}, \ \dots, \ a_{N-1}^{(k)}]^T$, $\boldsymbol{A} \triangleq \text{diag}[A_1, \dots, A_K]$ is the $K \times K$ matrix of signal amplitudes, $\boldsymbol{b}(i) \triangleq [b_1(i), \dots, b_K(i)]^T$ is the $K \times 1$ vector of the user's bits in the ith symbol interval and $\boldsymbol{w}(i) \triangleq [w_0(i), \dots, w_{N-1}(i)]^T$ is the $N \times 1$ vector of samples of the channel ambient noise whose elements are independent and identically distributed (i.i.d.) random variables having a non-Gaussian distribution.

2.1. Channel Noise Model

The statistical-physical models for electromagnetic radio disturbances proposed by Middleton (class A, B, and C) [4] are the most credited, but they are relatively complicated. The class B, modeling highly impulsive phenomena, is a particulary adequate noise model for wireless channels in the urban environment, but this model is described by two pdf functions, which are characterized by seven parameters (six generic plus one empirical). For that reason, an approximation for the class B should be considered. The α-stable model seems to be a very attractive model for this aim [11].

The symmetric α-stable ($S\alpha S$) random variables, with the location parameter equal to zero, are usually defined by its characteristic function

$$\varphi(\omega) = \exp(-\gamma|\omega|^{\alpha}), \quad (5)$$

where $\alpha \in (0, 2]$ is the *characteristic exponent* and $\gamma > 0$ is the scale parameter analogous to the variance, also called the *dispersion* of the $S\alpha S$ distribution [12]. The characteristic exponent α measures "heavyness" of the pdf tails. When the value of α decreases, the tails become heavier. For $\alpha = 1$, the stable distribution is the Cauchy distribution, while for $\alpha = 2$ is the Gaussian one. The stable distributions with $\alpha \ne 2$ have *algebraic* tails, and do not have second-order moments. However, for these distributions there exist finite moments of order $p < \alpha$, called *fractional lower order moments* (FLOM). The stable distributions fulfill *Generalized Central Limit Theorem* (for details see [13] and [12]).

3. ROBUST DECORRELATING MULTIUSER DETECTORS

The signal model (4) for a synchronous DS-CDMA system can be considered as a linear regression model with unknown K parameters $\theta_k \triangleq A_k b_k$, and can be rewritten as

$$\boldsymbol{r} = \boldsymbol{S}\boldsymbol{\theta} + \boldsymbol{w}, \quad (6)$$

where $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_K]^T$ is to be estimated (for simplicity we drop argument i). Classical solution of the linear regression problem is obtained using the least-squares (LS) method

$$\begin{aligned}\hat{\boldsymbol{\theta}}_{\mathrm{LS}} &= \arg\min_{\boldsymbol{\theta}} \sum_{n=0}^{N-1} \left(r_n - \sum_{k=1}^{K} s_n^{(k)} \theta_k \right)^2 \\ &= \arg\min_{\boldsymbol{\theta}} \|\boldsymbol{r} - \boldsymbol{S}\boldsymbol{\theta}\|^2. \end{aligned} \quad (7)$$

Differentiating cost function $J_{\mathrm{LS}}(\boldsymbol{\theta};\boldsymbol{r}) \triangleq \|\boldsymbol{r} - \boldsymbol{S}\boldsymbol{\theta}\|^2$ in (7), one obtains a linear system of equations that, assuming that signature waveforms of all users are linearly independent, has unique well known solution given by

$$\hat{\boldsymbol{\theta}}_{\mathrm{LS}} = (\boldsymbol{S}^T\boldsymbol{S})^{-1}\boldsymbol{S}^T\boldsymbol{r}. \quad (8)$$

The non-robust decorrelating detector consists of two stages: LS estimator (8) and hard-limiter

$$\hat{\boldsymbol{b}} = \mathrm{sgn}(\hat{\boldsymbol{\theta}}_{\mathrm{LS}}). \quad (9)$$

If the distribution of noise vector $\boldsymbol{w}$ is Gaussian, the LS estimate and the maximum likelihood estimate of $\boldsymbol{\theta}$ are identical, i.e. the LS estimator is optimal in the sense of achieving the Cramér-Rao lower bound (CRLB). However, even a slight deviation of the noise density from the Gaussian distribution causes that the LS estimator loses its optimality. In particular, the presence of impulses (*outliers*) in the noise waveform causes a substantial degradation of LS estimation accuracy.

In order to robustify the LS estimator against changes of the noise distribution, Huber [10] proposed to replace a sum of squared residuals by a sum of a less rapidly increasing penalty function $\rho(\cdot)$ of residuals

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_{n=0}^{N-1} \rho \left(r_n - \sum_{k=1}^{K} s_n^{(k)} \theta_k \right). \quad (10)$$

To find an estimate $\hat{\boldsymbol{\theta}}$ on the basis of observations $\boldsymbol{r}$ it is required now to solve the following nonlinear system of equations

$$\boldsymbol{S}^T\psi(\boldsymbol{r} - \boldsymbol{S}\boldsymbol{\theta}) = \boldsymbol{0}_K, \quad (11)$$

where function $\psi(\cdot)$ is the derivative of penalty function $\rho(\cdot)$, and $\psi(\boldsymbol{x}) \triangleq [\psi(x_1), \ldots, \psi(x_K)]^T$ for any $\boldsymbol{x} \in \mathbb{R}^K$. An appropriate choice of penalty function $\rho(\cdot)$ and corresponding function $\psi(\cdot)$ determines a specific robust estimator.

The minimax approach proposed in general case by Huber, and adopted by Wang and Poor in [5] for the case of minimax decorrelating detection, is derived with the assumption that the noise pdf belongs to the class of ε-contaminated Gaussian pdf's. In case of the α-stable channel noise, it is obvious that the choice of Huber penalty function is not optimal. In [7] and [8] this function was used for α-stable channel noise under the tacit and not justified formally assumption that it will mitigate the effect of an impulsive channel noise.

Further, we consider two approaches to synthesis of robust estimators: the maximum likelihood and the least l_p norm approach.

3.1. Maximum Likelihood Approach

The likelihood function of the received signal $\boldsymbol{r}$ under the true parameters $\boldsymbol{\theta}$ is given by

$$\begin{aligned} L_\theta(\boldsymbol{r}; f_\alpha) &\triangleq \ln \prod_{n=0}^{N-1} f_\alpha \left(r_n - \sum_{k=1}^{K} s_n^{(k)} \theta_k \right) \\ &= \sum_{n=0}^{N-1} \ln f_\alpha \left(r_n - \sum_{k=1}^{K} s_n^{(k)} \theta_k \right), \end{aligned} \quad (12)$$

where $f_\alpha(\cdot)$ is the pdf of channel noise samples. There exists only one interesting for us pdf that can be defined in closed form in the class of $S\alpha S$ distributions, namely the Cauchy distribution:

$$f_{\alpha=1}(x) = \frac{\gamma}{\pi(x^2+\gamma^2)}. \quad (13)$$

Therefore, we will assume that the Cauchy distribution is representative for all $S\alpha S$ distributions, and derive for it the ML-estimator. Maximization of likelihood function (12) is equivalent to solution of minimization problem (10) with the following penalty function

$$\rho_{\mathrm{ML}}(x) = -\ln f_\alpha(x)\big|_{\alpha=1} = \ln(x^2+\gamma^2). \quad (14)$$

Derivative of (14) is given by

$$\psi_{\mathrm{ML}}(x) = -\left.\frac{f'_\alpha(x)}{f_\alpha(x)}\right|_{\alpha=1} = \frac{2x}{x^2+\gamma^2}. \quad (15)$$

A similar approach to a different signal processing problem was presented in [14]. For the Cauchy noise, we obtain the optimal solution. This solution, however, is suboptimal for other values of α.

3.2. Least l_p Norm Approach

The least l_p norm approach is well known in the field of robust signal processing [15]. In the case of α-stable distributions, this approach has strong mathematical justification that comes from the Zolotarev theorem [12]. The *Minimum Dispersion* of error (MD) criterion for signals having α-stable distributions corresponds to the minimum mean square error (MMSE) criterion for signals with the finite variance. Zolotarev theorem states that the dispersion of $S\alpha S$ random variable is proportional to its FLOM of the order $1 < p < \alpha$. Thus, minimization of dispersion of the estimation error is equivalent to minimization of its pth order moment

$$\hat{\boldsymbol{\theta}}_{\mathrm{MD}} = \arg\min_{\boldsymbol{\theta}} \mathrm{E} \left| r_n - \sum_{k=1}^{K} s_n^{(k)} \theta_k \right|^p \quad 1 < p < \alpha. \quad (16)$$

Moreover, the FLOM ($1 < p < \alpha$) of an $S\alpha S$ RV describing the estimation error is a measure of distance between the true value and the estimated one in the l_p norm sense. By analogy to the LS solution (7), we can now formulate our robust estimation problem in the sense of the following least l_p norm criterion

$$\hat{\boldsymbol{\theta}}_{\text{LP}} = \arg\min_{\boldsymbol{\theta}} \sum_{n=0}^{N-1} \left| r_n - \sum_{k=1}^{K} s_n^{(k)} \theta_k \right|^p \quad 1 < p < \alpha. \tag{17}$$

From (17) it follows that the appropriate penalty function and its derivative are given by following expressions

$$\rho_{\text{LP}}(x) = |x|^p, \quad \psi_{\text{LP}}(x) = p\,|x|^{p-1}\text{sgn}(x). \tag{18}$$

4. IMPLEMENTATION OF ROBUST DETECTORS

As we mentioned above, finding of an estimates $\hat{\boldsymbol{\theta}}$ on the basis of observations $\boldsymbol{r}$ requires solution of nonlinear set of equations (11). This task can be done with use of iterative or recursive algorithms. In order to solve (11), we use the *Iteratively Reweighted Least Squares* (IRLS) algorithm and the *Recursive Weighted Least Squares* (RWLS) algorithm.

4.1. Iteratively Reweighted Least Squares Algorithm

The IRLS algorithm is very often used for calculation of robust estimates of linear regression parameters [15]. An initial estimate $\hat{\boldsymbol{\theta}}_0$ for this algorithm is the LS solution (8). In consecutive iterations $l = 1, 2, \ldots$ we firstly compute the vector of *residual errors*

$$\boldsymbol{e}_l = \boldsymbol{r} - \boldsymbol{S}^T \hat{\boldsymbol{\theta}}_l, \tag{19}$$

and then we create a diagonal *weight matrix*

$$\boldsymbol{W}_l = \text{diag}\left\{\phi(\boldsymbol{e}_l)\right\}, \tag{20}$$

where $\phi(\cdot)$ is a *weight function*, related to robustification function $\psi(\cdot)$, and defined as

$$\phi(x) \triangleq \frac{\psi(x)}{x}. \tag{21}$$

The weight matrix $\boldsymbol{W}_l$ is now used for updating the vector of estimated parameters

$$\hat{\boldsymbol{\theta}}_{l+1} = \left(\boldsymbol{S}^T \boldsymbol{W}_l \boldsymbol{S}\right)^{-1} \boldsymbol{S}^T \boldsymbol{W}_l \boldsymbol{r}. \tag{22}$$

Iterations are stopped, if $\|\hat{\boldsymbol{\theta}}_{l+1} - \hat{\boldsymbol{\theta}}_l\| \leq \delta$, where δ is a small number, or after arbitrarily specified number of steps.

There are two convergence conditions for the IRLS algorithm [15]; namely the weight function $\phi(x)$ should be: (1) nonincreasing with $|x|$, and (2) bounded for all x. Unfortunately, function $\phi_{\text{LP}}(x) = |x|^{p-2}$ does not meet the second condition and usually has been replaced by

$$\phi_{\text{LP}}(x) = \begin{cases} |x|^{p-2} & \text{for} \quad |x| > \epsilon, \\ \epsilon^{p-2} & \text{for} \quad |x| \leq \epsilon, \end{cases} \tag{23}$$

where ϵ is a small positive number. Computational complexity of the IRLS algorithm is of the order $(NK^2 + K^3)$.

4.2. Recursive Weighted Least Squares Algorithm

The adaptive structure of the decorralating multiuser detector was firstly proposed in [16], where the *Recursive Least Squares* (RLS) algorithm for recursive estimation of $\hat{\boldsymbol{\theta}}$ has been used. In this paper, we propose to use the RWLS algorithm for robust recursive estimation of $\hat{\boldsymbol{\theta}}$ in the presence of the α-stable channel noise. The task consist in minimization in each step n the following cost function

$$J_{\text{RWLS}}(n) \triangleq \sum_{j=0}^{n} \lambda^{n-j} \rho(e_j), \tag{24}$$

where $\lambda \in (0, 1]$ is the *forgetting factor* and e_n is the *a posteriori* estimation error

$$e_n = r_n - \sum_{k=1}^{K} s_n^{(k)} \hat{\theta}_{k,n} = r_n - \bar{\boldsymbol{s}}_n^T \hat{\boldsymbol{\theta}}_n, \quad n = 0, \ldots, N-1, \tag{25}$$

where $\hat{\boldsymbol{\theta}}_n$ is the vector of estimated parameters in nth step and $\bar{\boldsymbol{s}}_n \triangleq \left[s_n^{(1)}, \ldots, s_n^{(K)}\right]^T$. Following the derivation of the RLS algorithm [17, pp. 563-569], we obtain RWLS algorithm in which main recursion is given by

$$\hat{\boldsymbol{\theta}}_n = \hat{\boldsymbol{\theta}}_{n-1} + \boldsymbol{k}_n \xi_n, \tag{26}$$

where ξ_n is the *a priori* estimation error

$$\xi_n = r_n - \bar{\boldsymbol{s}}_n^T \hat{\boldsymbol{\theta}}_{n-1} \tag{27}$$

and $\boldsymbol{k}_n$ is the *Kalman gain vector*

$$\boldsymbol{k}_n = \frac{\boldsymbol{P}_{n-1} \bar{\boldsymbol{s}}_n}{\lambda\, \phi^{-1}(\xi_n) + \bar{\boldsymbol{s}}_n^T \boldsymbol{P}_{n-1} \bar{\boldsymbol{s}}_n}. \tag{28}$$

The matrix $\boldsymbol{P}_n$ is a recursive estimate of the matrix inverse to the *weighted autocorrelation matrix* of spreading signals. $\boldsymbol{P}_n$ is updated in consecutive steps n according to the recursion

$$\boldsymbol{P}_n = \frac{1}{\lambda}\left[\boldsymbol{P}_{n-1} - \boldsymbol{k}_n \bar{\boldsymbol{s}}_n^T \boldsymbol{P}_{n-1}\right]. \tag{29}$$

Specification of the $\phi(\cdot)$ function in (28) leads to special cases of the RWLS algorithm. For $\phi_{\text{ML}}(x) = \psi_{\text{ML}}(x)/x$ (see (15)), we have the *Recursive Maximum Likelihood* (RML) algorithm. Choosing $\phi_{\text{LP}}(x)$, we obtain the *Recursive Least l_p norm* (RLP) algorithm. The computational complexity of RWLS-type algorithms is of the order K^2.

5. SIMULATION RESULTS

In order to compare the proposed robust decorrelating detectors with the classical linear decorrelator, the DS-CDMA system with $K = 7$ active users and spreading gain $N = 31$ was simulated. The spreading sequence of each user is a shifted version of an m-sequence. The signal amplitudes A_k of all users were equal to 1. In all experiments, robust regression estimates were calculated using the IRLS algorithms (LP IRSL and ML IRLS) with the maximum number of iterations equal to 31, as well as using the RLP and RML algorithms with $\lambda = 1$. The value of the channel noise characteristic exponent α was 1.5. For the LP IRLS and RLP algorithms $p = 1.3$.

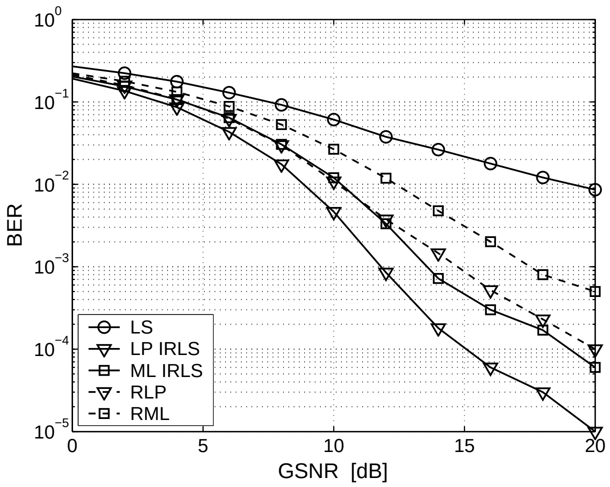

Fig. 1. Bit error rate of user 1 in DS-CDMA system with equal powers of received signals of all users; $N = 31$, $K = 7$, $\alpha = 1.5$

In Fig. 1, the bit error rate (BER) of the user 1 as function of the *Geometrical Signal-to-Noise Ratio* (GSNR) is depicted. GSNR is a generalization of the conventional SNR for signals with infinite variance [18], and for the user 1 is defined as

$$\mathrm{GSNR} = 10 \log \left(\frac{A_1^2}{2C_g^{(2/\alpha-1)} \gamma^{2/\alpha}} \right), \qquad (30)$$

where $C_g = \exp(C_e) \approx 1,78$. C_e is the Euler constant. It can be seen that for the $S\alpha S$ channel noise all robust detectors significantly outperform the classical linear (LS) decorrelator. Furthermore, for the assumed simulation parameters, iterative detectors perform better than adaptive ones, and LP detectors behave more reliable than ML detectors. The best performance is provided by the iterative LP detector. A more detailed simulation analysis shows that relations between performance of robust detectors depend simultaneously on the GSNR and the number K of active users with

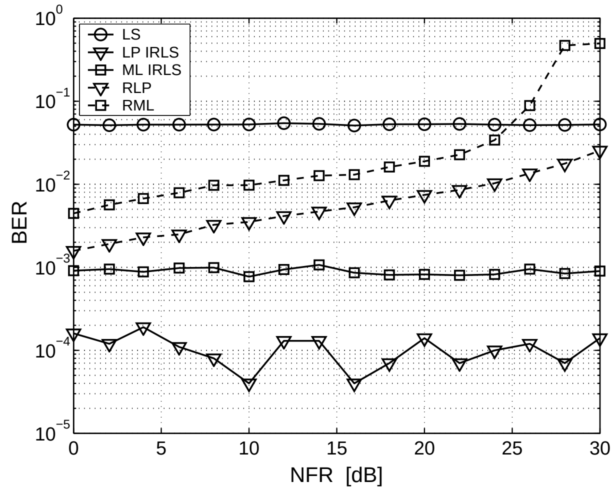

Fig. 2. Near-far resistance of decorrelating detectors; GSNR of user 1 is equal to 15 dB, $N = 31$, $K = 7$, $\alpha = 1.3$

equal signal powers. For $\mathrm{GSNR} = 15$ dB and $K > 15$, the best performance is offered by the ML adaptive detector based on the RML algorithm.

In Fig. 2, BER performance of the user 1 as function of the *Near-Far Ratio* (NFR) is shown. NFR is defined as a ratio of powers A_k^2, $k = 2, \ldots, 7$ of interfering users (in the considered case all interferers have the same power) to power A_1^2 of the desired user 1. GSNR of the user 1 is equal 15 dB. The characteristic exponent of $S\alpha S$ channel noise $\alpha = 1.3$. The parameter p in the case of LP detectors equals 1.2. From Fig. 2 it follows that the linear decorrelator and iterative robust decorrelating detectors are near-far resistant. Unfortunately, BER of robust adaptive detectors grows with NFR. For $\mathrm{NFR} > 25$ dB, the linear decorrelator outperforms the robust detector based on the RML algorithm. Poor performance of robust adaptive detectors results from the fact that RLP and RML algorithms (especially RML) have slow convergence for relatively large values of the *a priori* estimation error ξ_n arising in the case of a strong near-far effect. Appearance of many large values of ξ_n in a short data record (we have N samples of the received signal for each adaptation process connected with the ith symbol interval) causes that values of the weight function are close to zero, and for many steps the recursion (28) is not updated. This effect manifests more clearly in the case of the RML algorithm, because function $\phi_{\mathrm{ML}}(x)$ decreases faster than $\phi_{\mathrm{LP}}(x)$ for large values of $|x|$.

The BER curves of the user 1 as functions of characteristic exponent α of the channel noise are plotted in Fig. 3. The signal powers of all $K = 7$ users are equal, $\mathrm{GSNR} = 10$ dB. The parameter p for LP detectors was calculated according to the following rule: $p = \alpha - 0.1$. It is seen from

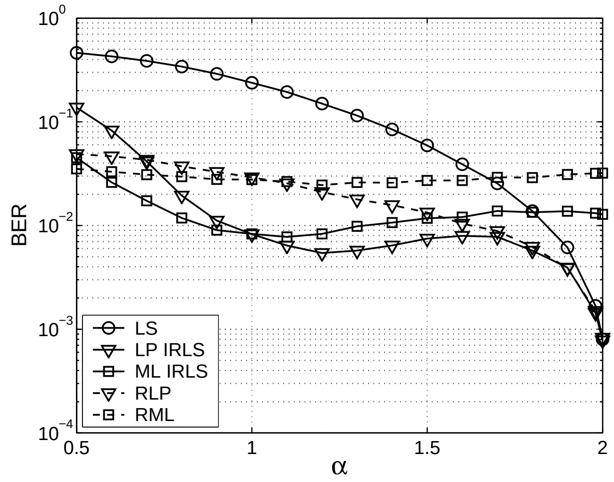

Fig. 3. Bit error rate of user 1 as function of characteristic exponent α; $N = 31$, $K = 7$, GSNR $= 10$ dB, equal powers of received signals of all users

Fig. 3 that performance of the linear decorrelator strongly depends on impulsiveness of the channel noise. The fastest changes of the BER curve for this detector are seen for $\alpha \in [1.8, 2]$. This confirms that the linear decorrelator is very sensitive to presence of an impulsive noise.

For $\alpha > 1$, LP detectors outperform ML detectors. For $\alpha < 1$, we have an opposite situation. This follows from the fact that LP detectors are designed only for $1 < p < \alpha$ (see (17)), and theoretically they should not operate when the characteristic exponent of the channel noise is less than 1. For $\alpha \in [1, 2]$, performance of ML detectors only slightly depends on α. This justifies the assumption that the Cauchy distribution is a representative distribution for the α-stable noises with $\alpha > 1$. For $\alpha \to 2$, LP detectors perform like the LS detector.

6. CONCLUDING REMARKS

In this paper, new robust decorrelating detectors for DS-CDMA communication systems with the non-Gaussian α-stable channel noise have been presented. The proposed detector schemes are derived using the least l_p norm criterion and the maximum likelihood criterion with assumption that the noise has the Cauchy distribution. The results of simulations have shown that robust detectors offer a significant performance improvement over the linear decorrelator. Furthermore, good performance of all proposed robust detectors is guaranteed for a wide range of values of the characteristic exponent α that determines impulsiveness of the channel noise. It also shown that the proposed iterative robust detectors are near-far resistant.

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